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Article

Developed Fall Detection of Elderly Patients in Internet of Healthcare Things

Omar Reyad[1,2], Hazem Ibrahim Shehata[1,3] and Mohamed Esmail Karar[1,4,*]

[1]College of Computing and Information Technology, Shaqra University, P. O. Box 33, Shaqra, 11961, Saudi Arabia
[2]Faculty of Computers and Artificial Intelligence, Sohag University, Sohag, 82524, Egypt
[3]Faculty of Engineering, Zagazig University, Zagazig, 44519, Egypt
[4]Faculty of Electronic Engineering, Menoufia University, Menouf, 32952, Egypt

*Corresponding Author: Mohamed Esmail Karar. Email: mkarar@su.edu.sa
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Abstract: Falling is among the most harmful events older adults may encounter. With the continuous growth of the aging population in many societies, developing effective fall detection mechanisms empowered by machine learning technologies and easily integrable with existing healthcare systems becomes essential. This paper presents a new healthcare Internet of Health Things (IoHT) architecture built around an ensemble machine learning-based fall detection system (FDS) for older people. Compared to deep neural networks, the ensemble multi-stage random forest model allows the extraction of an optimal subset of fall detection features with minimal hyperparameters. The number of cascaded random forest stages is automatically optimized. This study uses a public dataset of fall detection samples called SmartFall to validate the developed fall detection system. The SmartFall dataset is collected based on the acquired measurements of the three-axis accelerometer in a smartwatch. Each scenario in this dataset is classified and labeled as a fall or a non-fall. In comparison to the three machine learning models—K-nearest neighbors (KNN), decision tree (DT), and standard random forest (SRF), the proposed ensemble classifier outperformed the other models and achieved 98.4% accuracy. The developed healthcare IoHT framework can be realized for detecting fall accidents of older people by taking security and privacy concerns into account in future work.

Keywords: Elderly population; fall detection; wireless sensor networks; Internet of health things; ensemble machine learning

1 Introduction

One of the most widespread health disorders affecting elderly patients is falling. Fall is the second most frequent global cause of unexpected injuries and fatalities. According to the World Health Organization (WHO), a count rate of 30% of people over 65 years old suffer accidentally from one or more falls per year, and this rate increases to match a percentage of 50% for people over 80 years [1]. Thus, the fall required prompt medical assistance. When a fall happens, the fall detection system alerts the caregivers, minimizing the consequences for the patient. The fall detection system facilitates the patient's access to medical care while reducing the negative impacts of falls in realistic environments [2]. It is one of the primary factors behind the development of many intelligent fall-detection devices used today. The sensor(s) that gather the environmental and physiological info from the observed person is vital to any fall detection system. According to Mozaffari et al. [3], fall detection sensors can be categorized into three groups: ambient (or environmental), motion, and physiological. The elderly patient's internal environment is scanned using ambient sensors. The most typical ambient sensors monitor vision and sound (such as microphones and surveillance cameras). The most popular motion devices include magnetometers, gyroscopes, and accelerometers [4]. Accelerometers measure the rate of change in velocity with respect to time, whereas gyroscopes monitor angular velocity in three dimensions. Finally, magnetometers exist that can recognize orientation. The physiological sensors analyze critical human body indicators, including blood pressure, oxygen saturation, and temperature.

To evaluate the sensor data and search for specific patterns that identify fall events, fall detection algorithms use a variety of methodologies [5]. Innovative fall detection models can be used in the Internet of healthcare things framework based on ensemble machine learning (ML) techniques. Ensemble machine learning is a technique for obtaining harmony in predictions by combining the key features of two or more base models. Because ensemble learning minimizes the variation in prediction errors, the final predictive framework is more stable than the individual models that make up the ensemble [6]. An aggregated mapping function is produced via ensemble learning, which integrates the mapping functions encountered by various classifiers. Several approaches presented over the years employ multiple methods for generating this fusion. The three primary categories are bagging, stacking, and boosting ensemble learning methods. Bagging includes averaging the predictions from many decision trees fitted to various samples of the same dataset. When numerous distinct model types are provided to the same data, stacking is used to learn how to combine the predictions effectively. A weighted average of the predictions is produced by boosting, which entails adding ensemble members sequentially that corrects the predictions provided by earlier models [7]. Fig. 1 illustrates the various elements of the IoHT framework, including mobiles, apps, sensors, devices, and other healthcare workers.

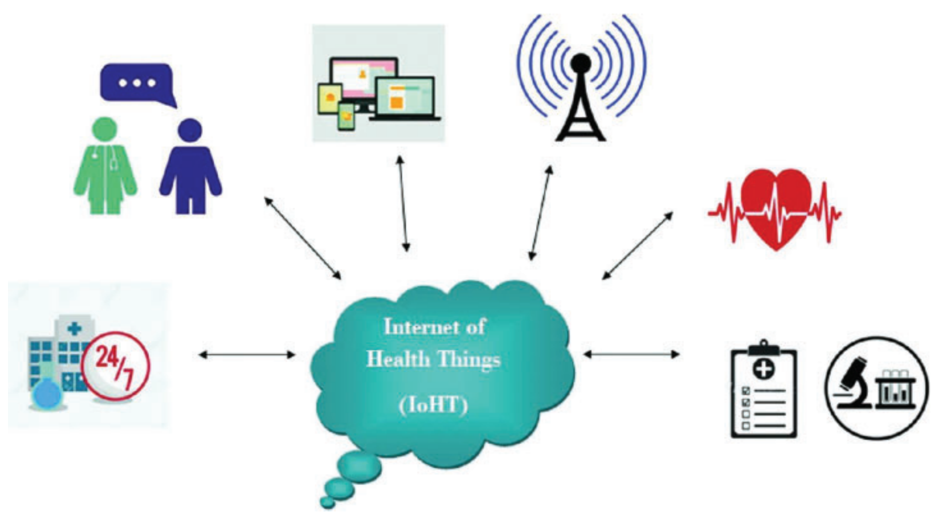

Figure 1: Schematic diagram of the Internet of health things (IoHT) components

In recent years, it has been found that the Internet of medical things (IoMT) and IoHT technologies can provide the computing capabilities required for fall detection systems [5,8]. Numerous IoHT-based fall detection methods for older adults have been presented in [9,10]. These IoHT-based frameworks may be more scalable than conventional structures, making them useful when there aren't enough healthcare professionals to handle large numbers of patients. The ambient platform is interconnected with various IoHT data sources from the health enterprise, including clinical and administrative applications, sensors, building systems, and medical equipment (and local systems). Patients can connect to the ambient platform using smartphones, remote devices, and increasingly embedded devices. These several different data sources will be used by the operations created by the ambient solution [11].

This study presents a modern IoHT-based fall detection model to help elderly patients' indoor healthcare. Following are the contributions summary of this study:

- Developing a framework for a simple and intelligent fall detection model for senior individuals based on wearable monitors and IoHT benefits.
- Implementing an ensemble-based classifier for the detection of accident falls of elderly patients, which is suitable for usage in the IoHT environments.
- Conducting a comparison analysis to verify that the proposed ensemble learning model outperforms conventional machine learning and deep learning (DL) classifiers.

The remainder of this research article is organized as follows. Section 2 presents relevant research on fall detection systems, including types of sensors, datasets, and machine and deep learning methods. Section 3 fully describes the proposed IoHT-based framework for fall detection of elderly patients using the developed ensemble random forest classifier. Overall results and evaluations of the extensive experiments carried out in this study and the discussions are demonstrated in Sections 4 and 5, respectively. Concluding remarks and main prospects of this study are finally given in Section 6.

2 Related Works

The evolution of modern technologies developed by researchers to identify and prevent falls in elderly patients has progressed significantly over the past few years. Several sophisticated techniques have been presented to tackle the issue of senior people falling [5,12,13]. These solutions include the use of IoT devices, ML and deep learning algorithms, and imaging training methods. Vision, sound, or a wearable device can all be used by intelligent fall detection tools to identify falls. Wearable fall detection sensor nodes mainly use gyroscopes, accelerometers, or a combination of different sensors. Most tools are monitoring and alarm systems designed to stop, identify and alert care providers to a fall event.

Additionally, a variety of wearable sensors have been developed in the framework of the IoT in healthcare to identify and prevent falls in elderly patients when they are at home. More than half of all hospitalizations for injuries are caused by older patients over 65. As a result, governments are investing more funds in improving fall detection appliances to decrease the cost of post-fall injury medical care and treatment [14].

The Whoops system is illustrated with scalable architecture in the work presented in [11]. The proposed design can track the cases of thousands of older people, catch falls, and inform caregivers. Additionally, many ML strategies for assessing the applicability of the detection system have been verified. The recognition accuracy of boosted decision trees (BDTs) was the highest among all the tested models. Yacchirema et al. in [15] suggested a new IoT-based solution for detecting senior persons' falls in enclosed locations. This approach integrates wireless sensor networks, smart devices, and cloud computing platforms. The system develops a new ML model each time a fall is identified using information from prior falls. With an identification accuracy of 92%, the proposed technique demonstrates a high level of falling recognition.

Instead of using Red, Green, and Blue (RGB) based cameras for capturing digital images of elderly persons, an intelligent wearable sensor is adopted, which offers privacy and powerful light intensity adjustments. To detect falls using an IoT framework, an integrated support vector machine (SVM) and a histogram of oriented gradients (HOG) have been applied [16]. After acquiring speckle noise binary images, the HOG algorithm extracts an individual's attributes. Then, using linear SVM, these attributes are classified to estimate the falling parameters. The authors employed long short-term memory (LSTM) model-based edge computing [17] to identify everyday patient activities, including fall incidents, in real-time. The edge computing platform can detect falls with an accuracy rate of 95.8% using actual human data stream processing. The study in [18] developed an intelligent IoTE-fall solution. The IoTE is an IoT platform built on a big data paradigm that employs ML processing algorithms based on ensemble random forest to detect falls in elderly persons in indoor surroundings. Three different types of falls—lateral, backward, and forward—were used to measure the system's performance. The overall performance metrics for the suggested system—98.72% recognition accuracy, 96.22% precision, and 94.60% sensitivity—show that it achieves a significant success rate.

For real-time monitoring of many populations, the authors suggested a centralized IOT-based fall detection system [19]. Monitoring a massive community can be done using various specialized devices, such as Arduino and Raspberry Pi boards. Overall, the suggested detection approach scored a 99.7% accuracy rate. To determine fall events using wearable IoT altimeter sensing devices, the authors of [20] introduced two temporal inference models, clustering models I and II. Based on these inferred models, the results for indoor fall monitoring of elderly persons were significant, yielding the maximum predictions overall accuracy of 98% for the suggested data classification model II. The authors reported a method for preventing falls in older adults [21] by developing and implementing a fall monitoring system incorporating ML to make decisions and the IoT to preserve data and send out alarms. The used ML algorithm has a 96% accuracy rate and is called XGBoost. It is well known for its speed and accuracy advantages.

The researchers of [22] developed a noise-tolerant FDS that functions well when missing values are in the data. The study combined recurrent neural networks (RNNs) with an underlying bidirectional long short-term memory (BiLSTM) structure to build FDS based on wearable sensors. The outcomes reveal that BiLSTM is a good model for handling missing values in wearable falling detection systems due to its ability to maintain long-term connectivity. The proposed study in [23] presented an improved Archimedes optimization method (IAOM) with DL augmented Fall detection model to distinguish between fall and non-fall events. The IAOM significantly enhances the detection of falls functionality by using a superior set of CapsNet hyperparameters. A radial basis function (RBF) structure is also used to identify the relevant class labels for the test images. According to the research results, the modified IAOM approach has an accurate score of 99.7%. A comparison of current fall detection approaches is shown in Table 1, depending on the related methodologies used.

Table 1: Summary of several fall detection techniques described in the previous studies

Method	Types of sensors	Dataset	Advantages	Disadvantages
BDTs [11]	Accelerometer & Gyroscope	SisFall	Small size of stored and transmitted data	Unnecessary emergency actions
BigML [15]	Accelerometer	SisFall	High success rate in fall detection	Error rate of 33%
HOG-SVM [16]	Deep sensor	Mixed	Accuracy of 98.1%	Still detection errors
LSTM [17]	MetaMotionR wearable	MobiAct	Real-time streaming with 95.8% accuracy	Data reduction
Ensemble- RF [18]	3D-axis accelerometer	SisFall	Accuracy of 98.72%	Several tri-axial devices
Linear classifier [19]	Accelerometer	tFall	Short response time	Need robust connectivity
Temporal inference [20]	Wearable altimeter sensor	Synthetic YouTube videos	Falls incident early warning	Methodological limitation
XGBoost [21]	Accelerometer & Gyroscope	SisFall	Increased accuracy and reduced false alarms	Young individuals' data included
RNN with BiLSTM [22]	Accelerometer & Gyroscope	SisFall & UP-Fall detection	Handle missing values in the data	Decrease incorrect predictions
CapsNet & Radial basis function [23]	Accelerometer	UR & Multiple Cameras Falls	Accuracy of 99.7%	Unimodal fusion model

3 Fall Dataset and Methodology

3.1 Fall Dataset

For this work, Texas State University's publicly available fall dataset was utilized as described in [24]. That dataset was collected from 14 healthy persons using a wearable smartwatch. They range in age from 21 to 60 years old, their lengths range from 1.52 to 1.98 meters, and their weights range from 45 to 104 kilograms. The participants generated fall-like scenarios to provide two dataset subclasses of fall and non-fall cases. The integrated accelerometer's readings in the x, y, and z coordinates are included in the entire dataset. The results are expressed in binary form, with ones and zeros marking instances of falls and non-falls, respectively. A majority of 183806 samples from the fall dataset are shown in Table 2, partitioned into two main files for the training and testing processes. The total testing samples are 91025, which includes 5025 fall instances and 86000 non-fall instances. Also, the table shows 92781 training samples, from which 8175 are for fall cases and 84606 for non-fall cases.

Table 2: The fall dataset for this research work is arranged into samples

Data samples	Falls	Non-falls	Overall
Training	8175	84606	92781
Testing	5025	86000	91025
Sum	13200	170606	183806

3.2 Ensemble Machine Learning Model

Random forest (RF) is a decision-tree ensemble technique with fewer hyper-parameters than deep neural networks [25]. It is developed in a cascade structure such that each level of the cascade receives feature information processed by the previous level, as depicted in Fig. 2. The levels of ensemble forest levels are estimated based on the processed input data automatically.

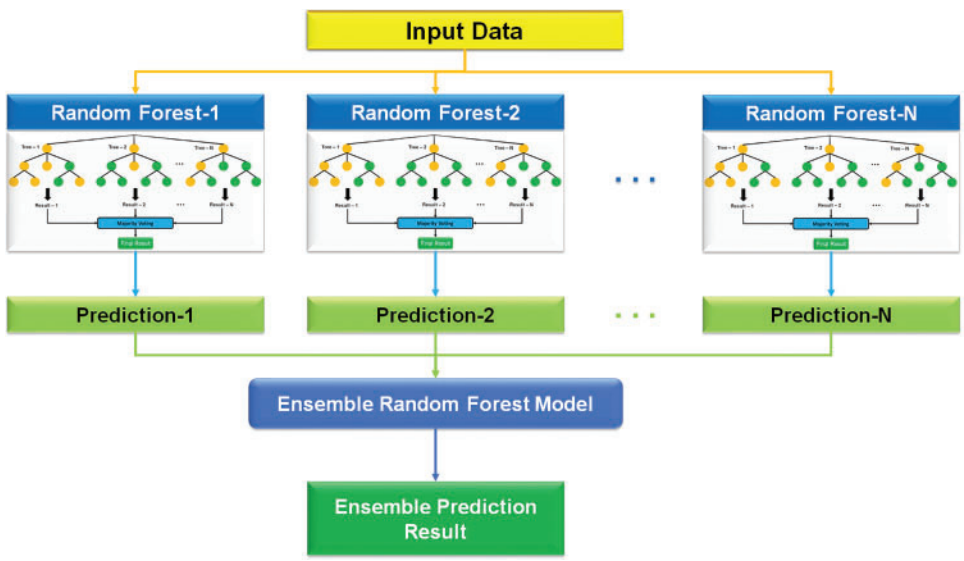

Figure 2: Schematic diagram of proposed ensemble random forest model

One level of the ensemble random forest presents an ensemble of random forests. Each random forest consists of 500 decision trees, where the number of trees is a hyperparameter for each forest. The number of input features d is randomly selected to achieve the best value of Gini for tree splitting [26]. Each RF can calculate a class distribution for a given instance by estimating the percentage of different classes of training samples at the leaf node where the instance is located and then averaging over all decision trees in the same RF. Each class vector is formed based on the estimated class distribution. The k-fold cross-validation technique [27,28] has been applied to generate the resulting class vector for each random forest to avoid overfitting the overall ensemble RF model.

3.3 Proposed Fall Detection System

Fig. 3 depicts the workflow of the developed fall detection system for old patients with smart-watches in healthcare IoT cloud services. The developed system assumed that the accelerometer sensing device is available in the smartwatch to measure the 3D-axis cartesian position of the patient to recognize the situation of non-fall and fall-accident situations. The three stages of the developed healthcare framework to detect fall accidents are described as follows.

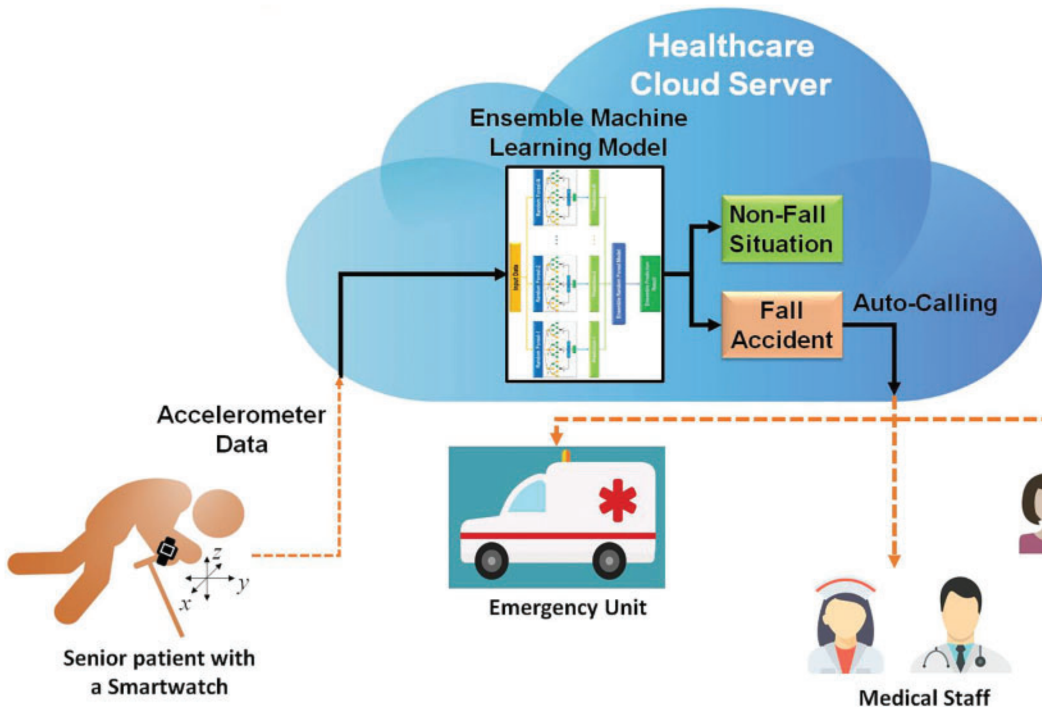

Figure 3: Workflow of the IoT-based healthcare framework developed in this study to detect the situation of fall accidents for older people with a smartwatch to send three-axis accelerometer data to a cloud server for analysis by proposed ensemble machine learning classifier

Firstly, elderly patients with a smartwatch and three-axis accelerometer readings are used to measure daily body motion in x-y-z coordinates, as described previously in [29]. The acquired readings of the senior patient are continuously monitored and sent via the Internet to a healthcare cloud server to be analyzed by the proposed ensemble machine learning model, as shown in Fig. 3.

Secondly, healthcare cloud services allow the monitoring, analyzing, and archiving of different forms of patient data, such as reports, signals, and images, without any need for high-cost computing resources at hospitals, clinics, and medical centers [30]. As shown in Fig. 2, obtained accelerometer data measurements of the patient motions are automatically classified using the proposed ensemble RF model.

Finally, the ensemble machine learning classifier gives two output cases: non-fall situation as a normal behavior and fall accident or emergency case. If a fall accident is detected, it is an emergency. The healthcare server automatically calls the emergency unit, medical staff (including caregivers and medical professionals), and family members, as depicted in Fig. 3.

3.4 Fall Detection Analysis

The gold-standard evaluation metrics for analyzing fall detection have been used to assess the proposed ensemble classifier. Cross-validation estimation is used to create a confusion matrix of 2×2 [31]. True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) are the four predicted outcomes of non-fall and fall classes. Additionally, four well-known classification metrics, namely accuracy, precision, recall (sensitivity), and F1-measure, have been calculated, as given in Eqs. (1)– (4).

$$accuracy = \frac{TP + TN}{TP + FP + FN + TN} 100\% \tag{1}$$

$$precision = \frac{TP}{TP + FP} \tag{2}$$

$$recall\ (sensitivity) = \frac{TP}{TP + FN} \tag{3}$$

$$F1 - measure = \frac{2\,(precision \times recall)}{precision + recall} \tag{4}$$

4 Experimental Results and Evaluation

The intended ensemble random forest models were deployed using the Tensorflow 2 and Keras packages [32]. The classification tests were carried out on a laptop with 16 GB of RAM and an Intel (R) Core (TM) i7-2.2 GHz processor. All investigations are performed using an NVIDIA 4GB graphics processing unit (GPU). A total of 92781 and 91025 samples are incorporated in two files of the public SmartFall dataset [24] for the training and testing processes, respectively. As shown in Table 2, the testing file contains 86000 patterns of non-fall cases, 17 times more than the 5025 instances of fall cases. All evaluated models' inputs were taken straight from the actual values of the accelerometer components (x, y, and z) in the employed dataset without any quantization or other modifications. In the suggested ensemble random forest classifier, three machine learning models—K-nearest neighbors (KNN), decision tree, and classic random forest—have been built and tested for identifying fall situations. This makes it possible to confirm the usefulness of the presented ensemble random forest model.

Based on the four-classification metrics—accuracy, precision, sensitivity or recall, and F1-score—presented in Table 3 are the quality assessment results for all evaluated machine learning classifiers (1–4). The suggested ensemble model successfully fulfilled the optimal classification metrics, yielding the highest accuracy score of 98.40%, as shown in Fig. 4. In addition, Table 4 shows a comparison between the suggested ensemble model's performance and that of other machine learning models from earlier studies that used the same publicly available dataset. By reaching the greatest accuracy score of 98.40%, the ensemble random forest classifier outperformed the typical deep learning model utilizing convolutional neural network (CNN) architecture, which had the lowest accuracy value of 86.00%. With a second-best accuracy score of about 97% for identifying fall occurrences, lightweight CNN can be used on mobile-embedded devices with constrained computational power. The proposed ensemble model attains the lowest computational complexity at testing time, and for certain problems of fall and non-fall classes in real-time scenarios, it can be the best choice.

Table 3: Evaluated performance metrics of all tested fall detection models in this study

Fall detection model	Class	Precision	Recall (Sensitivity)	F1-score	Accuracy (%)
K-nearest neighbors	Non-fall	0.958	0.969	0.956	92.90
	Fall	0.287	0.229	0.257	
Decision tree	Non-fall	0.959	0.908	0.928	88.10
	Fall	0.158	0.301	0.209	
	Non-fall	0.948	0.977	0.968	93.80
Random forest	Fall	0.346	0.202	0.252	
	Fall	0.810	0.120	0.221	
Proposed ensemble model	Non-fall	0.982	0.992	0.993	98.40
	Fall	0.831	0.719	0.778	

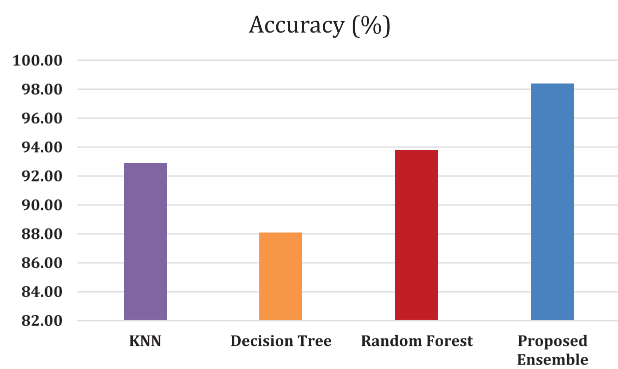

Figure 4: Results of fall detection models accuracy

Table 4: On the same dataset used in this study, comparative of ensemble forest's performance with other fall detection models from the literature

Fall detection model	Accuracy (%)
Deep learning model [24]	86.00
Long Short-Term Memory (LSTM) [33]	93.46
Lightweight convolutional neural network [34]	96.79
Proposed ensemble model	98.40

5 Discussion

As shown in Tables 3 and 4, the results of this work indicated that the proposed ensemble random forest classifier is accurate and effective in detecting fall cases in individuals compared to classical machine learning and deep learning classifiers. The public smartwatch dataset was used to estimate the suggested classifier's accuracy score, which is 98.40%. That is fair to assume to be the fundamental module of the proposed medical IoT system, shown in Fig. 3. The following are the principal factors contributing to the proposed ensemble random forest classifier's performance success. First, as shown in Fig. 2, the ensemble forest model's flow structure enables the generation of new features from the primary input features. Second, automatic ensemble random forest level or layer number estimate enables a strong matching to a challenging dataset, such as fall classification data. Finally, compared to other deep neural models, such as CNN, the number of parameters in the proposed ensemble classifier is smaller. As a result, the user can easily adjust the ensemble forest model's attributes. Even with early stopping constraints, the ensemble random forest classifier's effective layer estimations take a long time. However, the provided medical IoT-based design, as seen in Fig. 3, uses cloud computing services to make computational activities easier to complete. Additionally, the ensemble forest model's hyperparameter tuning can be carried out automatically by employing bio-inspired optimization techniques, including genetic algorithms (GAs) and particle swarm optimization (PSO) [35]. However, choosing the best set of model hyperparameters requires an optimization technique, which also takes time.

Recent healthcare IoT edge computing solutions [36] include advanced security and privacy capabilities for fall detection systems that are not considered in this study or other conventional fall detection devices [37]. Encryption and decryption operations should also be a part of trustworthy IoT-based healthcare platforms because they become crucial features for handling real-time tasks. Upcoming fall detection framework versions could be developed in areas of research like edge IoT layer [38], explainable and generalizable deep learning [39], and federated learning [40]. However, the real solution deployment of the suggested medical IoT architecture for fall detection of elderly persons remains valid and concise.

6 Conclusion and Future Work

Fall detection techniques are crucial for the health and well-being of older persons and, thus, are essential for their care. An investigation is required to develop solutions to reduce the harmful impacts of human falls. Such solutions would be more beneficial if they could be tightly integrated with healthcare management systems [41]. This study provides a straightforward and computationally effective solution for intelligent fall detection. The designed medical IoT solution makes use of inexpensive sensors that may be worn and implemented in homes and other institutions. With a remarkable accuracy score of 98.40%, the presented approach makes good use of an ensemble random forest algorithm and IoHT devices to identify the occurrence of older people falls in intelligent environments. For future works, other cutting-edge lightweight DL models for classification could be employed with different architectures and parameters to enhance the performance of the fall detection classifiers. Additionally, different types of datasets could be used for training and testing the new approaches.

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Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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